

Recent OSS Radiative Transfer Model Improvements and Application to Sounding

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EDR Algorithm Development and Instrument Design Testing Environments:

- Develop system with dual tasks in mind
 - Advance the state of Atmospheric and surface parameter retrieval algorithms
 - State of the art forward models
 - Both LBL and Fast model
 - Aid in the development and testing of new instrument designs
- Modularized software developed which allows for transparent updates/changes in retrieval algorithms and forward model development
- Can either simulate observations or ingest "real" measurement data
- **Optimal Spectral Sampling(OSS)** fast radiative transfer model primary RT model
 - Modular design does not limit testing other RT models including line-by-line(LBL)
- Examples of recent trade studies/algorithm development efforts
 - OSS comparison with OPTRAN with the JCDA: AIRS ILS
 - OSS validation studies using AIRS data
 - Testing retrieval algorithms with AIRS:
 - Both land and ocean environments
 - Temperature and Water vapor retrieval
 - Surface emissivity
 - Cloud property retrievals
 - HES instrument design trades
- **Development efforts centered around**
 - **Unified Retrieval(UR)** algorithm/infrastructure
 - **OSS** development/implementation

AER's Unified Retrieval (UR) Physical Algorithm Concept:

- Concept is to retrieve state parameters simultaneously with the ability to incorporate several data sources into the retrieval stream
- Initially applied and tested with DMSP Block 5D3 sensor suite
- Is the basis for the **NPOESS CrIMSS** and **CMIS** EDR algorithms. ATBD's available from the IPO (not most recent revisions)
 - http://140.90.86.6/IPOarchive/SCI/atbd/ATBD_V.02CorePhysicalInversonModule.pdf
 - http://140.90.86.6/IPOarchive/SCI/atbd/cris_atbd_03_09_01.pdf
- Incorporates state of the art **OSS** fast radiative transfer model
- Tested on recent Satellite/Aircraft based instruments

• AMSU	• SSMI	• AMSR
• AIRS	• NAST-I	

Optimal Spectral Sampling(OSS)

- OSS absorption parameterization leads to **fast** and **numerically accurate** RT modeling:
- OSS-based RT model can approach line-by-line calculations arbitrarily closely
 - **Adjustable numerical accuracy:**
 - Possibility of trade off between accuracy and speed
- Unsupervised training
 - **No empirical adjustment:**
- Provides flexible handling of (variable) trace molecular species
 - **Designed to handle large number of variable trace species** w/o any change to model – low impact on computational cost
 - Selection of variable trace gases at run time
- Memory requirements do not change whether we are dealing with one or more instruments
 - Execution speed primarily driven by total spectral coverage and maximum spectral resolution (not by number of instruments)
- **Accurate handling of multiple scattering** (cloudy radiance assimilation)
 - **OSS-SCAT**
- Used in:
 - **NPOESS/ CrIS, CMIS and OMPS (IR) retrieval algorithms**
 - **JCSDA CRTM**
- Beta version of OSS-based CRTM about to be tested at NCEP (Garand et al. 2001),
- Recent ITSC AIRS comparison (Saunders et al., 2005)
- Currently working on integrating into **MODTRAN** (AFRL-sponsored effort)
- NASA's Mars Fundamental Research Program: OSS forward model has been developed for the Thermal Emission Spectrometer (TES) onboard the Mars Global Surveyor spacecraft (Christensen et al. 2001).

OSS tables in use for many instrument designs

- Microwave:

• AMSU(NOAA and EOS)	• AMSR
• SSMI, SSMI/S	• ATMS(NPOESS,NPP)
• CMIS(NPOESS)	
- IR:

• CrIS(NPOESS,NPP)	• AIRS
• NASTI(Airborne)	• HES(PORD)

Optimal Spectral Sampling (OSS) Method:

OSS fast forward model

• Channel radiance for inhomogeneous atmospheric path represented by weighted sum over specific frequencies or "nodes"

$$\bar{R} = \int_{\Delta n} f(n) R(n) dn \equiv \sum_{i=1}^N w_i R(n_i); \quad ?_i \in \Delta n$$

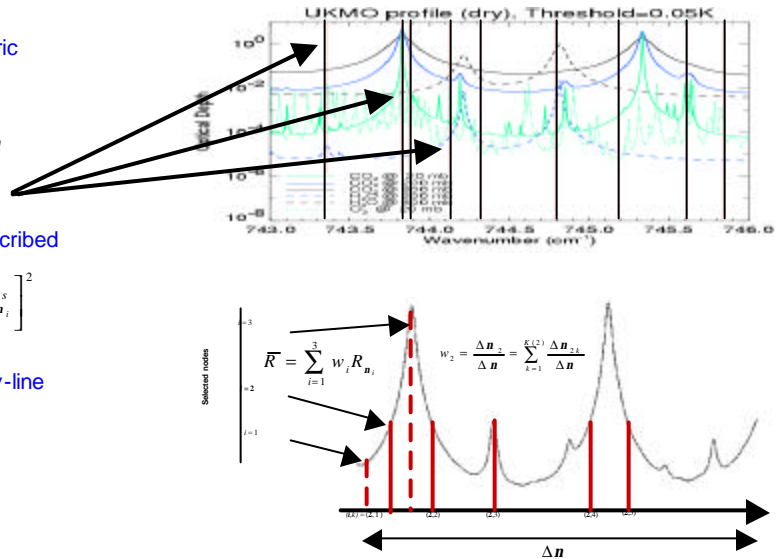
• Automated search for smallest subset of **nodes** and weights for which the error is less than a prescribed tolerance

$$\left\{ (n_i, w_i) \mid i = 1, \dots, N \right\} \quad e_N = \sum_s \left[R^s - \sum_{i=1}^N w_i R_{n_i}^s \right]^2$$

• In the training, radiances calculated with a line-by-line model (e.g. LBLRTM, GENLN) using a globally representative ensemble of atmospheres, surface conditions, viewing angles, etc..

• Radiance training fast

• Planck function accounted for exactly

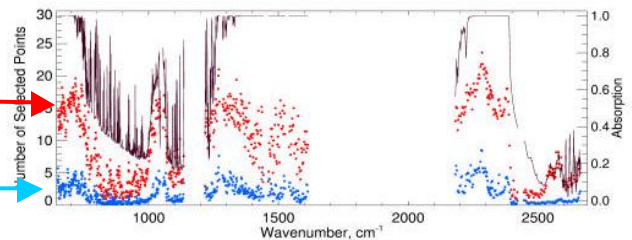


Localized versus Generalized Training

• **Localized training** (benchmark) operates on individual channels, one at a time – node redundancy due to overlapping ILS

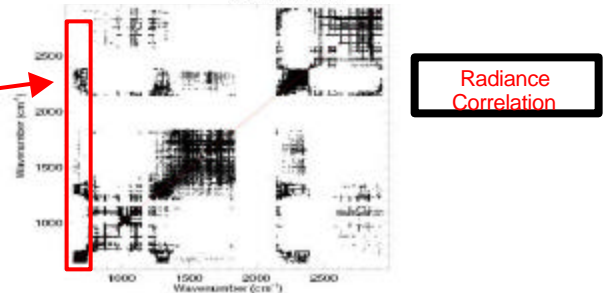
• AIRS (2378 channels):

- Average # nodes per channel: ~9 nodes/channel
- Total number of nodes/number of channel (i.e. no redundancy) = 1.9 nodes/channel



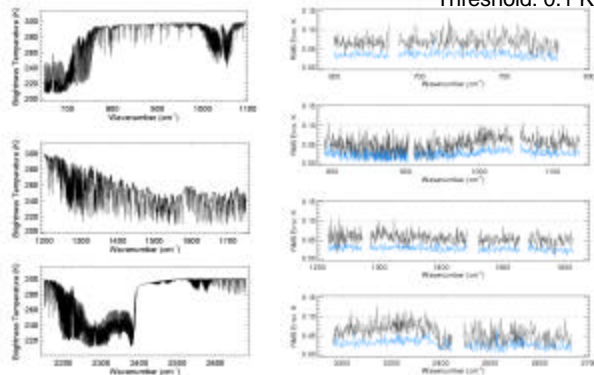
• **Generalized Training** operates on groups of N channels (up to full channel set)

- Exploits node-to-node correlation to minimize total number of nodes across a spectral domain
- Results in significant increase in number of points in any given channel



OSS Applied to the AIRS ILS

Threshold: 0.1 K

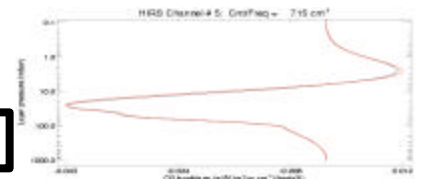


- Training performed with 260 profiles Threshold: 0.05K
- Validation performed using 52 independent profiles
- Both sets obtained from ECMWF
- Errors for two tolerance values, 0.1K and 0.05K

Jacobians

- Required for retrievals/assimilations
- Calculated at little added computational cost
 - Simultaneous with radiance
- Analytic Jacobians, not finite diff.
 - Temperature
 - All variable gases
 - Surface properties
 - Future: Cloud properties in adding/doubling scheme

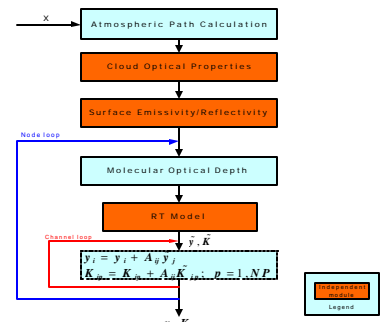
O₃ Jacobian for 715cm⁻¹



RTM structure

- Main loop is the node loop
 - Internal channel loop to update channel radiance and Jacobians
 - Similar structure adopted for CRTM
- LUT of k abs stored for all relevant molecules as a function of temperature
 - Self broadening included for water vapor
 - Maximum brightness temperature error with current LUT < 0.05K in infrared and < 0.01K in microwave
- Use simple monochromatic RT model (clear or scattering)
 - Jacobians (required for retrieval applications) are straightforward in the clear-sky (e.g. CrIS ATBD)

OSS Forward Model



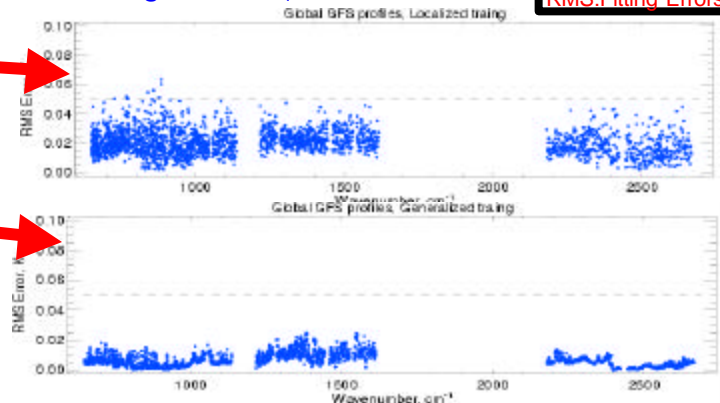
OSS Generalized Training: AIRS ILS

RMS:Fitting Errors

- Localized training (0.05K accuracy):
 - ~2 nodes/channel
 - ~5000 monochromatic calculations for full AIRS channel set

- Generalized training:
 - ~0.1 node/channel
 - Reduces number of monochromatic calculations to ~250

Speed gain ~ 20 compared to localized training for AIRS



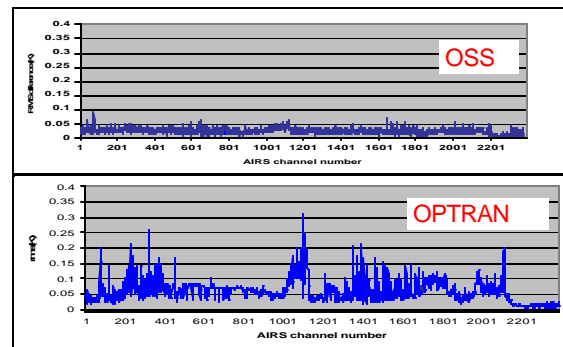
OSS in JCSDA CRTM: Comparison with OPTRAN

- OSS compared with OPTRAN, AIRS ILS
 - Timing
 - Accuracy

Timings based upon 48 profiles, 7 angles (336 total)

	OPTRAN-V7 Forward, Jacobian + Forward	OPTRAN-comp Forward, Jacobian + Forward	OSS Jacobian + Forward
AIRS	7m20s, 22m36s	10m33s, 35m12s	3m10s
HIRS	4s, 13s	5s, 17s	9s

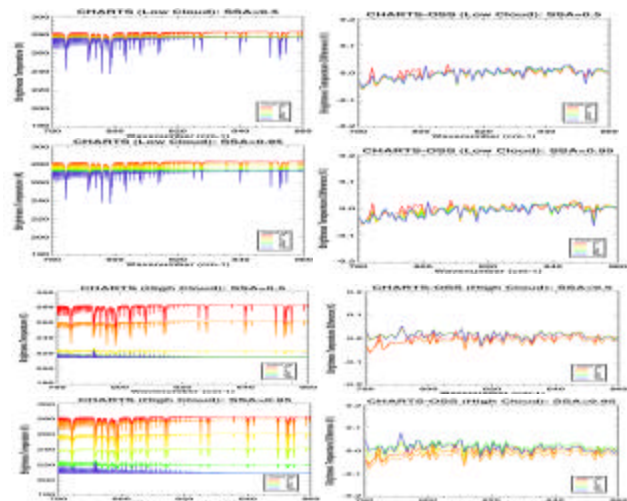
- OSS incorporated into CRTM
 - Both MW and IR will be available



Comparison with LBL calculations
Radiance residual RMS

OSS-SCAT/CHARTS Comparison: Cloudy Radiance Validation

- CHARTS (Moncet and Clough, 1997)
 - Fast adding-doubling scheme for use with LBLRTM
 - Uses tables of layer reflection/transmission as a function of absorption computed at runtime
- OSS-SCAT:
 - Single wavelength version of CHARTS (no spectral interpolation)
- Cloudy validation:
 - Molecular absorption from 740-900 cm⁻¹ domain
 - 1 cm⁻¹ boxcars, thermal only
 - Cloud extinction OD range: 0-100
- Example:
 - 780-860 cm⁻¹
 - Low cloud case (925-825 mb)
 - High cloud case (300-200 mb)



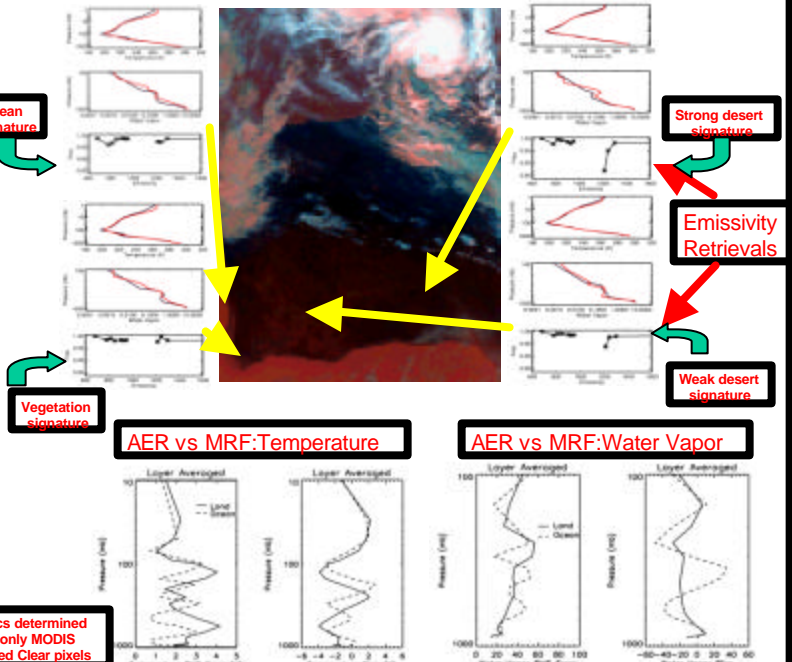
Clear Sky Retrievals: AIRS Measurements

- Non-linear iterative physical retrieval method with radiometric and geophysical constraints
- Simultaneous retrieval of required atmospheric and surface parameters. Well suited for modern high resolution hyper-spectral instruments
- Empirical Orthogonal Function (EOF) decomposition of retrieval parameters
 - Reduce the dimensionality of the inversion problem.
 - Stabilizes inversion and reduces the time needed per retrieval.
- Within this framework: basic quantity retrieved is the difference between state vector and background state vector in reduced dimension space (Rodgers 1976)

$$\Delta \tilde{x}_{i+1} = (\tilde{K}_i^T S_y^{-1} \tilde{K}_i + \Lambda^{-1})^{-1} \tilde{K}_i^T S_y^{-1} (y_0 - y_i + \tilde{K}_i \Delta \tilde{x}_i)$$

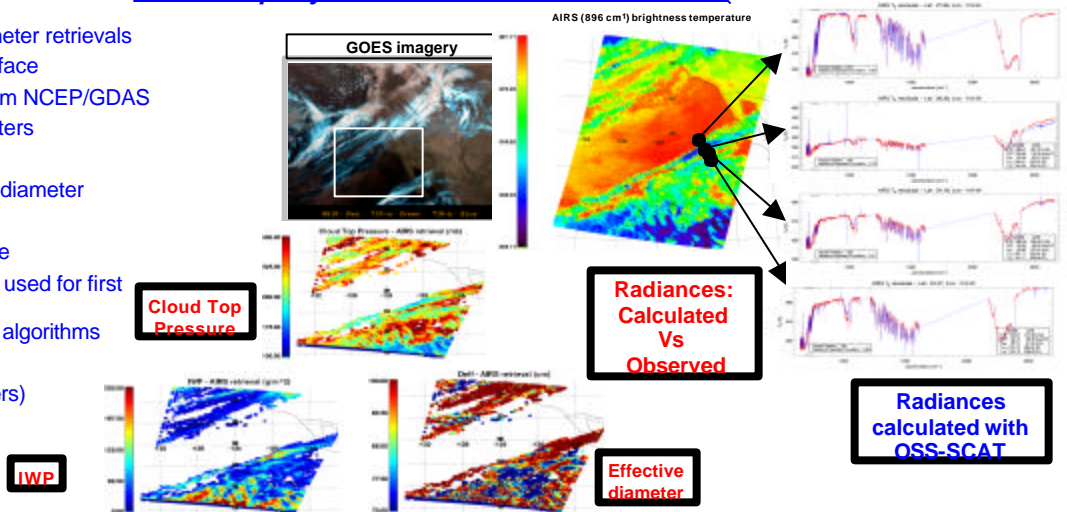
$$\Delta \tilde{x}_{i+1} = (\tilde{K}_i^T S_y^{-1} \tilde{K}_i + \Lambda^{-1})^{-1} \tilde{K}_i^T S_y^{-1} (y_0 - y_i + \tilde{K}_i \Delta \tilde{x}_i)$$

- Parameters retrieved
 - Temperature/water vapor profiles
 - Skin temperature
 - Surface Emissivity (12 hinge points)
 - Ozone scaling factor
- Retrievals performed on each FOV
 - No cloud clearing nor MW first guess
 - Climatologic first guess/background



Cloud Property Retrievals: AIRS Measurements

- Single FOV cloud parameter retrievals
- Fix Atmosphere and surface
 - profiles and SST from NCEP/GDAS
- Retrieved cloud parameters
 - Cloud top/thickness
 - Ice particle effective diameter
 - Ice water Path (IWP)
 - Effective temperature
- MODIS based retrievals used for first guess
 - AER SERCAA cloud algorithms
- RTM:
 - OSS-SCAT (100 layers)
 - 4 stream



Retrievals In Node Space: Generalized OSS

- Variational retrieval methods:
 - Average channel uses ~150 nodes
 - Mapping Jacobians from node to channel space partially offsets speed gain
- Alternative:
 - Operate directly in node space

$$\mathbf{y}^m = \mathbf{A} \tilde{\mathbf{y}}^m \rightarrow \hat{\mathbf{y}}^m = \mathbf{H} \mathbf{y}^m$$

$$\mathbf{d} \mathbf{x}_{n+1} = (\mathbf{K}_n^T \mathbf{S}_e^{-1} \mathbf{K}_n + \mathbf{S}_x^{-1}) \mathbf{K}_n^T \mathbf{S}_e^{-1} \left[(\mathbf{y}_n - \mathbf{y}^m) + \mathbf{K}_n \mathbf{d} \mathbf{x}_n \right],$$

where,

$$\mathbf{y} = \mathbf{A} \tilde{\mathbf{y}} \text{ and } \mathbf{K} = \mathbf{A} \tilde{\mathbf{K}}$$

$$\tilde{\mathbf{y}}^m = (\mathbf{A}^T \mathbf{S}_e^{-1} \mathbf{A})^{-1} \mathbf{A}^T \mathbf{S}_e^{-1} \mathbf{y}^m$$

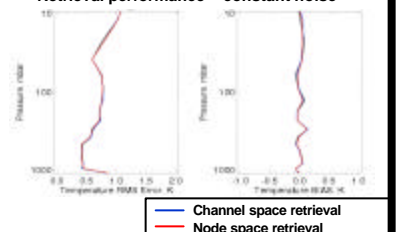
$$\tilde{\mathbf{S}}_e^{-1} = \mathbf{A}^T \mathbf{S}_e^{-1} \mathbf{A}$$

$$\mathbf{d} \mathbf{x}_{n+1} = (\tilde{\mathbf{K}}_n^T \tilde{\mathbf{S}}_e^{-1} \tilde{\mathbf{K}}_n + \mathbf{S}_x^{-1}) \tilde{\mathbf{K}}_n^T \tilde{\mathbf{S}}_e^{-1} \left[(\tilde{\mathbf{y}}_n - \tilde{\mathbf{y}}^m) + \tilde{\mathbf{K}}_n \mathbf{d} \mathbf{x}_n \right]^{n+1}$$

Equivalent to

$$\mathbf{d} \mathbf{x}_{n+1} = (\mathbf{K}_n^T \mathbf{S}_e^{-1} \mathbf{K}_n + \mathbf{S}_x^{-1}) \mathbf{K}_n^T \mathbf{S}_e^{-1} \left[(\mathbf{A} \mathbf{H} \mathbf{y}_n - \tilde{\mathbf{y}}^m) + \mathbf{K}_n \mathbf{d} \mathbf{x}_n \right]$$

Retrieval performance – constant noise



- Need strategy for handling input dependent noise
 - Scene temperature dependence (clear/cloudy)
 - worse in SW band
 - Cloud clearing noise amplification
- H-transformation not overly sensitive to noise
 - For clear retrievals: sufficient to update noise covariance regionally